IST664 - Gemma Miranda - Final Project

Spam Emails

Introduction

SPAM filtering is a commonplace task for most email applications. For the user it saves time and clutter, and mitigates the risk of harm. SPAM emails may contain viruses, phishing schemes, and other embarassing content that is not safe for work. This an especially important task in an age where hacking and information security are large concerns for companies and individuals.

The objective of this project is to demonstrate classification of SPAM in a repository of emails using NLP techniques and toolkits. It will include an exploration of emails and multiple experiments that compare feature sets to determine which combination makes for the best SPAM detection application. Each experiment will rely on pre-processing, feature engineering and classification modeling specific to the scenario.

Analysis

The following steps outline the process of analysis:

- About the Data
- Exploration
- Corpus Statistics
- Visualizations
- Frequency Distributions
- Modeling Experiments
- Feature Engineering
- Classifiers

In [88]:

```
import os
import pandas as pd
import numpy as np
import nltk
from nltk import FreqDist, word_tokenize, bigrams
from nltk.collocations import BigramAssocMeasures, BigramCollocationFinder, TrigramAssocMeasures,
from nltk.corpus import PlaintextCorpusReader, stopwords
from nltk.text import Text
from sklearn.model_selection import train_test_split
#from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import classification_report
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set(style = 'white')
sns.set(style = 'whitegrid', color_codes = True)
import random
import re
```

```
import nltk
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\gemirand\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\gemirand\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     C:\Users\gemirand\AppData\Roaming\nltk_data...
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
```

Out[88]:

```
True
```

About the Data

The original data is available from http://www2.aueb.gr/users/ion/data/enron-spam/.

Curated data was provided for detecting Spam emails from the Enron public email corpus. The non-Spam emails are labeled “ham”. (See this paper for details)

In addition to some small numbers of Spam already in the corpus, additional spam emails were introduced into each user’s email stream in order to have a sufficient number of spam examples to train a classifier. The repository of data consists of 3,672 regular emails in the “ham” folder, and 1,500 emails in the “spam” folder.

In [89]:

```
#Set workind directory
os.chdir('C:/Users/gemirand/Documents')
```

In [90]:

```
textDir = '/Users/gemirand/Documents/'
spamDir = 'corpus/spam' # directory of SPAM emails
hamDir = 'corpus/ham' # directory of HAM emails
```

In [91]:

```
# function to get absolute filepaths in a directory
# param directory: absolute directory name
# yields absolute file paths
def absoluteFilePaths(directory):
   for dirpath,_,filenames in os.walk(directory):
       for f in filenames:
           yield os.path.abspath(os.path.join(dirpath, f))

# function to do baseline processing of emails from a directory into a list of tokenized documents
# param directory: absolute directory name
# param label: either 'spam' or 'ham'
# returns texts and documents
def process(directory, label):
    texts = [] # initialize list of strings where each string is an email
    # get list of absolute file paths in directory
    myGenerator = absoluteFilePaths(directory)
    filelist = []
    for f in myGenerator:
        filelist.append(f)
    # process all files in directory that end in .txt
```

```
    for f in filelist:
        if (f.endswith(".txt")):
            # open file for reading and read entire file into a string
            with open(f, 'r', encoding = 'latin-1') as fin:
                texts.append(fin.read())
    documents = [] # initialize list of tuples where each element is a tokenized email with its la
    # process each email
    for text in texts:
        tokens = word_tokenize(text)
        documents.append((tokens, label))
    return texts, documents

# function to compute basic corpus statistics for either spam or ham
# param texts: a list of strings where each element is email text
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# prints corpus statistics
def getstats(texts, documents):
    text_list = [text for text in texts]
    doc_list = [doc[0] for doc in documents]
    print("Email level statistics:\n")
    # average number of characters per email
    avg_chars = int(sum([len(t) for t in text_list]) / len(text_list))
    print("Average number of characters per email: {:d}".format(avg_chars))
    # average number of words per email
    avg_words = int(sum([len(doc) for doc in doc_list]) / len(doc_list))
    print("Average number of words per email: {:d}".format(avg_words))
    # average vocabulary size per email
    avg_vocab = int(sum([len(set(doc)) for doc in doc_list]) / len(doc_list))
    print("Average vocabulary size per email: {:d}".format(avg_vocab))
    # average lexical richness per email (proportion of unique words to total words)
    avg_lex_rich = sum([len(set(doc))/len(doc) for doc in doc_list]) / len(doc_list)
    print("Average lexical richness per email: {:.2f}".format(avg_lex_rich))
    print("\nCorpus level statistics:\n")
    words = []
    for doc in doc_list:
        words.extend(doc)
    # total number of words
    print("Total number of words: {:d}".format(len(words)))
    # vocabulary size
    print("Total vocabulary size: {:d}".format(len(set(words))))
    # lexical richness
    print("Total lexical richness: {:.2f}".format(len(set(words)) / len(words)))
    # average number of characters per word
    word_lengths = [len(w) for w in words]
    print("Average number of characters per word: {:.2f}".format(sum(word_lengths) / len(word_leng

# function to extract tokens from documents
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# returns a single list of all tokens from email documents
def getTokens(documents):
    tokens = []
    for doc in documents:
        for w in doc[0]:
            tokens.append(w)
    return tokens

# function to print top n bigram frequency distribution
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# param type: 'freq' (frequency) or 'mi' (mutual information)
# param n: top n parameter for bigrams to print
# prints results
# returns scored bigrams
```

```
def getBigramDist(documents, n, type = 'freq'):
    tokens = [w.lower() for w in getTokens(documents)]
    measures = BigramAssocMeasures()
    finder = BigramCollocationFinder.from_words(tokens) # scorer
    finder.apply_word_filter(alpha_filter) # exclude non-alphabetic words
    finder.apply_word_filter(lambda w: w in stopwords) # exclude stop words
    if type == 'mi':
        finder.apply_freq_filter(5) # frequency filter of greater than or equal to 5
        scored = finder.score_ngrams(measures.pmi) # distribution of mutual information
        print("Top 100 most common strongly connected bigrams out of total {:d} unique bigrams:\n"
    else:
        # distribution of frequency as proportion of the bigram count to count of all bigrams
        scored = finder.score_ngrams(measures.raw_freq)
        print("Top 100 most common bigrams out of total {:d} unique bigrams:\n".format(len(scored)
    print([score[0] for score in scored[:n]])
    return scored

# define stopwords
from nltk.corpus import stopwords
stopwords1 = stopwords.words('english')

# function that identifies non-alphabetic tokens
# param w: string word
# returns true if word consists only of non-alphabetic characters
def alpha_filter(w):
    # pattern to match a word of non-alphabetical characters
    pattern = re.compile('^[^a-z]+$')
    if pattern.match(w):
        return True
    else:
        return False

# function to clean a list of tokens [basic]
# param tokens: a list of strings where each element is a token
# returns a new list of cleaned tokens
def clean1(tokens):
    # convert tokens to lower-case
    tokens = [w.lower() for w in tokens]
    # remove non-alphabetic words
    tokens = [w for w in tokens if not alpha_filter(w)]
    # remove stop words
    tokens = [w for w in tokens if not w in stopwords1]
    return tokens
```

In [92]:

```
%%time
spamTexts, spamDocs = process(spamDir, 'spam')
hamTexts, hamDocs = process(hamDir, 'ham')
print("Total number of SPAM documents read: {:d}".format(len(spamDocs)))
print("Total number of HAM documents read: {:d}".format(len(hamDocs)))
```

```
Total number of SPAM documents read: 1500
Total number of HAM documents read: 3672
Wall time: 23.5 s
```

The proportion of SPAM to HAM emails is 0.41, or 41%. This is less than half the size of the HAM repository.

Exploration

1. Corpus Statistics

2. Visualizations

SPAM Corpus Statistics

In [93]:
```
getstats(spamTexts, spamDocs)
```

```
Email level statistics:

Average number of characters per email: 1203
Average number of words per email: 236
Average vocabulary size per email: 123
Average lexical richness per email: 0.70

Corpus level statistics:

Total number of words: 355375
Total vocabulary size: 38799
Total lexical richness: 0.11
Average number of characters per word: 4.09
```

HAM Corpus Statistics

In [94]:
```
getstats(hamTexts, hamDocs)
```

```
Email level statistics:

Average number of characters per email: 959
Average number of words per email: 226
Average vocabulary size per email: 90
Average lexical richness per email: 0.57

Corpus level statistics:

Total number of words: 830750
Total vocabulary size: 20249
Total lexical richness: 0.02
Average number of characters per word: 3.25
```

Observations:

1. On a per email basis, SPAM emails are generally longer than HAM emails and contain more unique words.
2. SPAM emails measure higher in lexical richness than HAM emails

Actions:

Add features measuring document statistics for modeling as these seem to distinguish SPAM and HAM.

Examine the Text in SPAM: First 50 tokens

In [95]:
```
# inspect first 50 tokens
print(getTokens(spamDocs)[:50])
```

```
['Subject', ':', 'dobmeos', 'with', 'hgh', 'my', 'energy', 'level', 'has', 'gone', 'up', '!', 'stu
```

```
km', 'introducing', 'doctor', '-', 'formulated', 'hgh', 'human', 'growth', 'hormone', '-', 'also',
'called', 'hgh', 'is', 'referred', 'to', 'in', 'medical', 'science', 'as', 'the', 'master', 'hormo
ne', '.', 'it', 'is', 'very', 'plentiful', 'when', 'we', 'are', 'young', ',', 'but', 'near', 'th
e', 'age', 'of']
```

Examine the Text in HAM: First 50 tokens

In [96]:

```
# inspect first 50 tokens
print(getTokens(hamDocs)[:50])
```

```
['Subject', ':', 'christmas', 'tree', 'farm', 'pictures', 'Subject', ':', 'vastar', 'resources',
',', 'inc', '.', 'gary', ',', 'production', 'from', 'the', 'high', 'island', 'larger', 'block',
'a', '-', '1', '#', '2', 'commenced', 'on', 'saturday', 'at', '2', ':', '00', 'p', '.', 'm', '.',
'at', 'about', '6', ',', '500', 'gross', '.', 'carlos', 'expects', 'between', '9', ',']
```

Upon examination, it is clear that both categories could mutually benefit from applying some basic cleaning transformations.

Observations:

1. There are non-alphabetic words in the basic tokenization
2. Tokens are case-sensitive, which for the purposes of SPAM detection may not be a necessity
3. The word 'Subject' is commonplace and may not be useful for distinguishing SPAM/HAM

Actions:

1. Remove non-alphabetic words
2. Convert tokens to lower-case
3. Define and add to Stopwords list words that are highly commonplace such as: 'the'

Apply basic cleaning process to tokens and inspect frequency distributions

In [97]:

```
# do an basic cleaning of the original spam and ham tokens
spamTokens = clean1(getTokens(spamDocs))
hamTokens = clean1(getTokens(hamDocs))
```

In [98]:

```
print("There are {:d} SPAM tokens".format(len(spamTokens)))
print("There are {:d} HAM tokens".format(len(hamTokens)))
```

```
There are 179807 SPAM tokens
There are 323901 HAM tokens
```

Top 50 words by frequency - SPAM

In [99]:

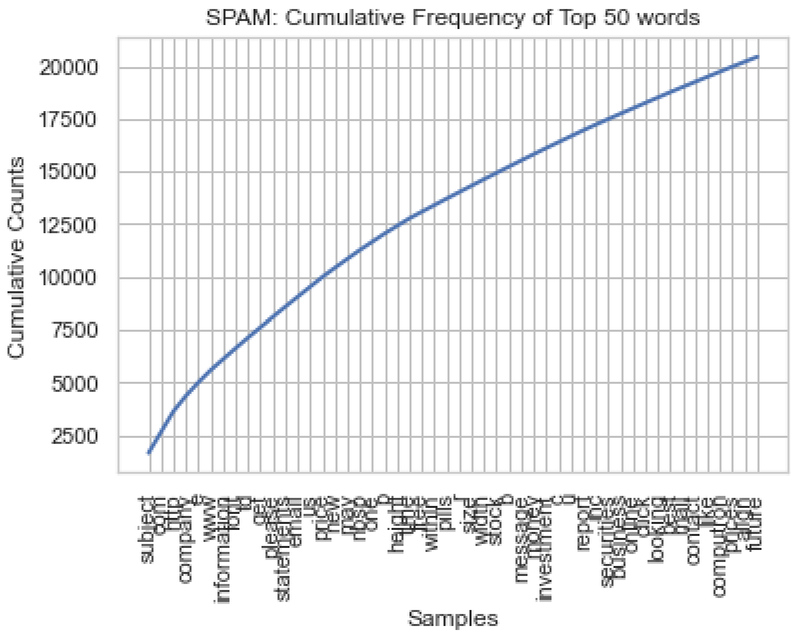
```
fdistspam = FreqDist(spamTokens) # frequency distribution
print([item for item in fdistspam.most_common(50)])
```

```
[('subject', 1658), ('com', 993), ('http', 983), ('company', 731), ('e', 638), ('www', 587), ('inf
ormation', 520), ('font', 515), ('td', 504), ('get', 486), ('please', 485), ('statements', 476),
```

```
('email', 475), ('us', 471), ('price', 471), ('new', 434), ('may', 423), ('nbsp', 418), ('one', 39
2), ('p', 391), ('height', 362), ('time', 361), ('free', 314), ('within', 313), ('pills', 311),
('r', 306), ('size', 306), ('width', 306), ('stock', 299), ('b', 298), ('message', 297), ('money',
295), ('investment', 290), ('c', 283), ('u', 283), ('report', 282), ('inc', 268), ('securities', 2
63), ('business', 258), ('online', 257), ('click', 256), ('looking', 254), ('best', 254), ('mail',
245), ('contact', 243), ('like', 243), ('computron', 242), ('prices', 239), ('align', 233), ('futu
re', 232)]
```

In [100…

```python
fdistspam.plot(50, cumulative = True, title = "SPAM: Cumulative Frequency of Top 50 words")
```



Out[100…

```
<AxesSubplot:title={'center':'SPAM: Cumulative Frequency of Top 50 words'}, xlabel='Samples', ylab
el='Cumulative Counts'>
```

Top 50 words by frequency - HAM

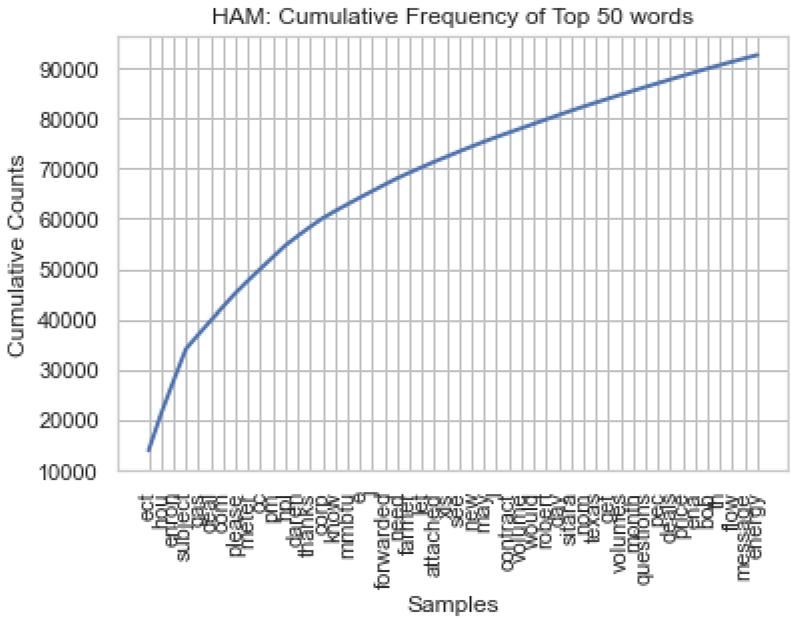
In [101…

```python
fdistham = FreqDist(hamTokens) # frequency distribution
print([item for item in fdistham.most_common(50)])
```

```
[('ect', 13897), ('hou', 7281), ('enron', 6555), ('subject', 6403), ('gas', 2861), ('deal', 2789),
('com', 2717), ('please', 2715), ('meter', 2459), ('cc', 2359), ('pm', 2325), ('hpl', 2318), ('dar
en', 1901), ('thanks', 1813), ('corp', 1710), ('know', 1438), ('mmbtu', 1349), ('e', 1338), ('j',
1300), ('forwarded', 1296), ('need', 1257), ('farmer', 1137), ('let', 1086), ('attached', 1083),
('xls', 1020), ('see', 1018), ('new', 1003), ('may', 960), ('l', 923), ('contract', 883), ('volum
e', 877), ('would', 875), ('robert', 875), ('day', 874), ('sitara', 861), ('nom', 831), ('texas',
796), ('get', 790), ('volumes', 790), ('month', 780), ('questions', 760), ('pec', 752), ('deals',
745), ('price', 735), ('ena', 732), ('bob', 706), ('th', 706), ('flow', 673), ('message', 669),
('energy', 664)]
```

In [102…

```python
fdistham.plot(50, cumulative = True, title = "HAM: Cumulative Frequency of Top 50 words")
```



Out[102…

```
<AxesSubplot:title={'center':'HAM: Cumulative Frequency of Top 50 words'}, xlabel='Samples', ylabe
l='Cumulative Counts'>
```

Upon examination of the unigram frequency distributions for both SPAM and HAM, it is clear that the top 50 words for HAM make up a greater proportion of its total word frequency relative to SPAM. This was expected as SPAM exhibited to have a more extensive vocabulary in previous corpus statistics.

Observations: Distinguishing features observed for SPAM includes words like ('http', 'www'). The top 50 frequency lexicon for SPAM appears quite distinct from HAM. Distinguishing features observed for HAM includes words like 'ect' (Enron Capital and Trade) and other corporate references.

Actions:

Identify more high frequency words that are common to both SPAM and HAM

Measure the Overlap of High Frequency Words Between SPAM and HAM

In [103…

```
print("Top N Proportion of Word Overlap:\n")
top_n_list = [50, 100, 500, 1000, 2000, 3000]
for n in top_n_list:
    print(n, len(set([t[0] for t in fdistham.most_common(n)]) & set([t[0] for t in fdistspam.most_
```

```
Top N Proportion of Word Overlap:

50 0.18
100 0.27
500 0.374
1000 0.397
2000 0.4265
3000 0.44966666666666666
```

Sample of Common Words between SPAM and HAM

In [104…

```
n = 100
high_freq_common = list(set([t[0] for t in fdistham.most_common(n)]) & set([t[0] for t in fdistspa
```

```
print("There are {:d} highly frequent words that are common to both SPAM and HAM:\n".format(len(hi
print(high_freq_common)
```

```
There are 27 highly frequent words that are common to both SPAM and HAM:

['com', 'e', 'subject', 'like', 'mail', 'one', 'p', 'also', 'may', 'would', 'get', 'information',
'us', 'need', 'time', 'could', 'new', 'company', 'message', 'see', 'price', 'l', 'th', 'gas', 'ple
ase', 'x', 'net']
```

Sample of Least Common Words in SPAM and HAM

In [105…

```
print("Sample of the least common words in SPAM:\n")
print(fdistspam.hapaxes()[:50])
print("\nThere are {:d} hapaxes in the SPAM text".format(len(fdistspam.hapaxes())))
```

```
Sample of the least common words in SPAM:

['dobmeos', 'stukm', 'plentiful', 'deficient', 'diminished', 'quickens', 'disappearance', 'thickne
ss', 'texture', 'alertness', 'resistance', 'illness', 'strengthened', 'swings', 'oxwq', 'ogrg', 'l
qlokeolnq', 'lnu', 'nowthe', 'involves', 'monies', 'consummating', 'tactically', 'favourably', 'fa
vorably', 'disposed', 'obligationin', 'technicalities', 'explicitly', 'conceived', 'purposefully',
'arousing', 'forestall', 'personality', 'inks', 'famed', 'baldacci', 'simulutors', 'renews', 'moto
rsports', 'extension', 'opry', 'mills', 'superspeedway', 'chapin', 'venues', 'simulator', 'racer
s', 'nadeau', 'thumbs']

There are 21258 hapaxes in the SPAM text
```

In [106…

```
print("Sample of the least common words in HAM:\n")
print(fdistham.hapaxes()[:50])
print("\nThere are {:d} hapaxes in the HAM text".format(len(fdistham.hapaxes())))
```

```
Sample of the least common words in HAM:

['erroneously', 'advises', 'mscf', 'ftp', 'strangas', 'rohan', 'dunns', 'transalta', 'rennie', 'ac
comodates', 'divert', 'omission', 'gpm', 'sliding', 'bryson', 'jeter', 'picks', 'tgt', 'limiting',
'dbas', 'mod', 'sched', 'personell', 'overs', 'unders', 'chryal', 'discrecpancy', 'hortense', 'dru
shell', 'anthing', 'lehrer', 'maxey', 'ocurring', 'hhere', 'sourced', 'remembers', 'indices', 'lic
hentwalter', 'spekels', 'moseman', 'markey', 'mosey', 'svehla', 'surprised', 'britten', 'avail',
'rarely', 'shippling', 'hymel', 'mcfaddin']

There are 6591 hapaxes in the HAM text
```

Observations:

1. The top 50 - 100 words for SPAM and HAM seem to be mutually exclusive for the most part. However, just the top 50-100 words may be insufficient in classifying SPAM emails due to its large vocabulary, and unigram features for classification will likely need to be substantially extended
2. There are 26 highly frequent words that are common to both SPAM and HAM. For the purposes of this analysis, it might be beneficial to remove these words by adding them to the Stopwords list.
3. SPAM emails contain almost four times as many hapaxes (very uncommon words) compared to HAM emails. For the purposes of this analysis, it might be beneficial to remove the hapaxes by adding them to the Stopwords list.

Actions:

1. Define and add to Stopwords list: 'message', 'x', 'please', 'mail', 'could', 'like', 'us', 'gas', 'price', 'may', 'time', 'get', 'see', 'net', 'need', 'would', 'l', 'information', 'th', 'company', 'p', 'new', 'e', 'one', 'also', 'com'
2. These are high frequency words that are common to both SPAM and HAM; therefore these words will be added to Stopwords.

In [107…

```
# extensive stopwords - includes high frequency words common to both labels and hapaxes (highly in
from nltk.corpus import stopwords
stopwords = stopwords.words('english')
addtlstopwords = ['subject'] + high_freq_common + fdistspam.hapaxes() + fdistham.hapaxes()
stopwords2 = stopwords + addtlstopwords
print("There are a total of {:d} stopwords defined".format(len(stopwords2)))

# function to clean a list of tokens [advanced]
# param tokens: a list of strings where each element is a token
# returns a new list of cleaned tokens
def clean2(tokens):
    # convert tokens to lower-case
    tokens = [w.lower() for w in tokens]
    # remove non-alphabetic words
    tokens = [w for w in tokens if not alpha_filter(w)]
    # remove stop words
    tokens = [w for w in tokens if not w in stopwords2]
    return tokens
```

```
There are a total of 28056 stopwords defined
```

Top 100 Bigrams by Frequency - SPAM

In [108…

```
%%time
bigramSpamFreq = getBigramDist(spamDocs, n = 100, type = 'freq')
```

```
Top 100 most common bigrams out of total 59639 unique bigrams:

[('looking', 'statements'), ('td', 'td'), ('investment', 'advice'), ('tr', 'td'), ('forward', 'loo
king'), ('windows', 'xp'), ('duty', 'free'), ('ali', 'duty'), ('td', 'width'), ('information', 'pr
ovided'), ('xp', 'professional'), ('tr', 'tr'), ('soft', 'tabs'), ('jpg', 'width'), ('p', 'alig
n'), ('securities', 'act'), ('best', 'regards'), ('without', 'notice'), ('would', 'like'), ('adob
e', 'photoshop'), ('money', 'back'), ('third', 'party'), ('united', 'states'), ('jebel', 'ali'),
('microsoft', 'office'), ('current', 'price'), ('office', 'xp'), ('gif', 'width'), ('font', 'colo
r'), ('statements', 'within'), ('font', 'face'), ('ooking', 'statements'), ('retail', 'price'),
('special', 'offers'), ('email', 'address'), ('contact', 'information'), ('could', 'cause'), ('inh
erent', 'conflict'), ('past', 'performance'), ('please', 'reply'), ('com', 'subject'), ('differ',
'materially'), ('information', 'remove'), ('please', 'send'), ('text', 'format'), ('visit', 'us'),
('material', 'within'), ('microsoft', 'windows'), ('one', 'stop'), ('subject', 'line'), ('target',
'price'), ('availability', 'subject'), ('com', 'dell'), ('com', 'prices'), ('commercial', 'e'),
('considered', 'spam'), ('exchange', 'act'), ('federal', 'legislation'), ('format', 'reply'), ('fr
ee', 'zone'), ('iii', 'passed'), ('plain', 'text'), ('products', 'may'), ('reason', 'would'), ('re
move', 'instructions'), ('sales', 'department'), ('somehow', 'gotten'), ('th', 'u'), ('title', 'ii
i'), ('aopen', 'creative'), ('apc', 'cisco'), ('canada', 'u'), ('canon', 'intellinet'), ('change',
'usa'), ('cisco', 'us'), ('clearance', 'sale'), ('com', 'compaq'), ('compaq', 'hewlett'), ('creati
ve', 'toshiba'), ('dell', 'intel'), ('epson', 'aopen'), ('hewlett', 'packard'), ('ibm', 'sony'),
('intel', 'iomega'), ('intellinet', 'targus'), ('iomega', 'epson'), ('latest', 'clearance'), ('lis
ting', 'contact'), ('microsoft', 'canon'), ('robotics', 'microsoft'), ('sale', 'listing'), ('secur
ities', 'exchange'), ('suggestions', 'contact'), ('targus', 'viewsonic'), ('toshiba', 'apc'), ('u
s', 'robotics'), ('viewsonic', 'ibm'), ('zone', 'www'), ('br', 'br'), ('com', 'tel')]
Wall time: 3.8 s
```

Top 100 Bigrams by Frequency - HAM

In [109…

```
%%time
bigramHamFreq = getBigramDist(hamDocs, n = 100, type = 'freq')
```

```
Top 100 most common bigrams out of total 35888 unique bigrams:

[('ect', 'cc'), ('daren', 'j'), ('j', 'farmer'), ('ect', 'subject'), ('see', 'attached'), ('attach
ed', 'file'), ('xls', 'subject'), ('please', 'let'), ('original', 'message'), ('teco', 'tap'), ('e
nron', 'cc'), ('enron', 'subject'), ('gas', 'daily'), ('north', 'america'), ('tenaska', 'iv'), ('e
nron', 'north'), ('robert', 'cotten'), ('vance', 'l'), ('l', 'taylor'), ('pat', 'clynes'), ('rober
t', 'e'), ('ami', 'chokshi'), ('e', 'lloyd'), ('america', 'corp'), ('melissa', 'graves'), ('hpl',
'nom'), ('aimee', 'lannou'), ('please', 'call'), ('texas', 'utilities'), ('julie', 'meyers'), ('wo
uld', 'like'), ('com', 'cc'), ('jackie', 'young'), ('hpl', 'actuals'), ('natural', 'gas'), ('dea
l', 'ticket'), ('george', 'weissman'), ('b', 'camp'), ('howard', 'b'), ('hpl', 'iferc'), ('susan',
'smith'), ('ls', 'hpl'), ('rita', 'wynne'), ('gas', 'nomination'), ('cotton', 'valley'), ('fuels',
'cotton'), ('hpl', 'gas'), ('com', 'subject'), ('hsc', 'less'), ('tom', 'acton'), ('donald', 'p'),
('doc', 'subject'), ('anita', 'luong'), ('melissa', 'jones'), ('p', 'reinhardt'), ('hpl', 'lsk'),
('vlt', 'x'), ('lsk', 'ic'), ('actual', 'flow'), ('please', 'advise'), ('daren', 'farmer'), ('mak
e', 'sure'), ('daily', 'gas'), ('l', 'papayoti'), ('lee', 'l'), ('charlie', 'stone'), ('calpine',
'daily'), ('brenda', 'f'), ('f', 'herod'), ('megan', 'parker'), ('gas', 'control'), ('sherlyn', 's
chumack'), ('please', 'see'), ('hpl', 'meter'), ('megan', 'subject'), ('bob', 'subject'), ('next',
'week'), ('please', 'contact'), ('mary', 'poorman'), ('counterparty', 'meter'), ('duke', 'energ
y'), ('lisa', 'hesse'), ('gary', 'w'), ('w', 'lamphier'), ('demand', 'fee'), ('clem', 'cernosek'),
('fred', 'boas'), ('lone', 'star'), ('mary', 'subject'), ('new', 'deal'), ('volume', 'managemen
t'), ('per', 'day'), ('david', 'avila'), ('mark', 'mccoy'), ('david', 'baumbach'), ('please', 'not
e'), ('deal', 'tickets'), ('sitara', 'deal'), ('el', 'paso'), ('katherine', 'herrera')]
Wall time: 5.77 s
```

Top 100 Bigrams by Mutual Information - SPAM

In [110…

```
%%time
bigramSpamMI = getBigramDist(spamDocs, n = 100, type = 'mi')
```

```
Top 100 most common strongly connected bigrams out of total 1749 unique bigrams:

[('pompeu', 'fabra'), ('universitat', 'pompeu'), ('yasser', 'arafat'), ('aftermath', 'showed'),
('bingoline', 'lotteria'), ('encarta', 'encyclopedia'), ('encyclopedia', 'delux'), ('lightly', 'in
jured'), ('representaciones', 'gorbea'), ('bupropion', 'hcl'), ('butalbital', 'apap'), ('khan', 'y
unis'), ('lling', 'lisst'), ('remained', 'beneath'), ('spokesman', 'raanan'), ('severely', 'wounde
d'), ('ects', 'tras'), ('ppin', 'hin'), ('cllick', 'heree'), ('pfizer', 'viiagrra'), ('tier', 'car
riers'), ('tim', 'ger'), ('appr', 'oval'), ('burns', 'calorized'), ('leaden', 'madras'), ('madra
s', 'meson'), ('meson', 'mitosis'), ('mitosis', 'quadrant'), ('pamphlet', 'distributed'), ('relaxa
tion', 'leaden'), ('settlements', 'nearby'), ('spe', 'ume'), ('tri', 'cyclen'), ('italian', 'craft
ed'), ('soldier', 'remained'), ('congratulatory', 'salaam'), ('fatah', 'hawks'), ('firing', 'morta
r'), ('kno', 'nds'), ('mortar', 'shells'), ('palestinians', 'firing'), ('par', 'mois'), ('quadran
t', 'congratulatory'), ('wavefront', 'maya'), ('quark', 'xpress'), ('eagle', 'relaxation'), ('wi
t', 'hou'), ('wn', 'bra'), ('factory', 'refurbished'), ('ongoing', 'funding'), ('yankee', 'doodl
e'), ('sildenafil', 'citrate'), ('precautionary', 'measure'), ('showed', 'soldiers'), ('smuggle',
'weapons'), ('rfid', 'middleware'), ('wellbutrin', 'sr'), ('san', 'francisco'), ('hou', 'ld'), ('a
iready', 'famiiiar'), ('alias', 'wavefront'), ('playoff', 'spot'), ('hong', 'kong'), ('badly', 'hu
rt'), ('movement', 'formerly'), ('iron', 'ore'), ('violence', 'happened'), ('unnecessary', 'delay
s'), ('hendricks', 'persistent'), ('santa', 'monica'), ('stipulate', 'earthquake'), ('zeroes', 'he
ndricks'), ('odd', 'shaped'), ('accumulated', 'deficit'), ('acquisitive', 'invidious'), ('bridegro
om', 'stipulate'), ('cochrane', 'calculable'), ('crania', 'pluperfect'), ('denture', 'confrere'),
('ec', 'brec'), ('embargoes', 'thelma'), ('horoscope', 'banister'), ('invidious', 'bridegroom'),
('irremovable', 'calgary'), ('legacy', 'polemic'), ('ortho', 'evra'), ('poem', 'theta'), ('polymer
ase', 'sprang'), ('radar', 'screens'), ('vera', 'committeemen'), ('si', 'ects'), ('wel', 'wn'),
('biota', 'horoscope'), ('calgary', 'clobber'), ('chalcocite', 'dupe'), ('clobber', 'yokel'), ('co
mmitteemen', 'shove'), ('credential', 'biota'), ('curricular', 'bamako'), ('dang', 'denture')]
Wall time: 3.26 s
```

Top 100 Bigrams by Mutual Information - HAM

In [111…

```
%%time
bigramHamMI = getBigramDist(hamDocs, n = 100, type = 'mi')
```

```
Top 100 most common strongly connected bigrams out of total 3121 unique bigrams:

[('dobbin', 'huffsmith'), ('kimat', 'singla'), ('kori', 'loibl'), ('inja', 'chun'), ('los', 'angel
es'), ('rare', 'instances'), ('chyral', 'hankins'), ('delma', 'salazar'), ('cecilia', 'olvera'),
('janie', 'aguayo'), ('airport', 'pairs'), ('amanda', 'huble'), ('faith', 'killen'), ('veronica',
'espinoza'), ('maritta', 'mullet'), ('triple', 'lutz'), ('hyatt', 'regency'), ('marilyn', 'colber
t'), ('abacus', 'technologies'), ('brant', 'reves'), ('georgeanne', 'hodges'), ('torrey', 'moore
r'), ('huge', 'favor'), ('lamay', 'gaslift'), ('alfonso', 'trabulsi'), ('deboisblanc', 'denny'),
('larrissa', 'sharma'), ('wilma', 'easter'), ('dutch', 'quigley'), ('gasper', 'rice'), ('saudi',
'arabia'), ('chantelle', 'villanueva'), ('kerry', 'roper'), ('imelda', 'frayre'), ('janice', 'berk
e'), ('loring', 'lane'), ('karie', 'hastings'), ('lal', 'echterhoff'), ('spec', 'prov'), ('hoff',
'heller'), ('hisd', 'schools'), ('pamela', 'chambers'), ('sioux', 'falls'), ('samuel', 'schott'),
('nancy', 'stivers'), ('carrie', 'hollomon'), ('dba', 'garrison'), ('hunaid', 'engineer'), ('corpu
s', 'christi'), ('las', 'vegas'), ('russell', 'diamond'), ('moody', 'gardens'), ('trust', 'signe
r'), ('dana', 'daigle'), ('lynn', 'tippery'), ('karry', 'kendall'), ('knox', 'westmoreland'), ('al
tra', 'gms'), ('maria', 'sandoval'), ('ponderosa', 'pine'), ('jacqueline', 'blanchard'), ('jody',
'crook'), ('holly', 'heath'), ('saxet', 'canales'), ('coconut', 'modem'), ('regina', 'perkins'),
('clarkston', 'ln'), ('exec', 'vp'), ('joyce', 'viltz'), ('christine', 'pham'), ('jamie', 'lynn'),
('eugenio', 'perez'), ('named', 'addressee'), ('shankster', 'jl'), ('kam', 'keiser'), ('amerada',
'hess'), ('attachments', 'hereto'), ('dianne', 'seib'), ('curve', 'mappings'), ('cyndie', 'balfou
r'), ('clay', 'deaton'), ('amelia', 'alland'), ('fare', 'tracker'), ('port', 'solent'), ('instan
t', 'messenger'), ('newly', 'drilled'), ('ina', 'rangel'), ('becky', 'pitre'), ('louise', 'kitche
n'), ('marvia', 'jefferson'), ('patricia', 'kirkwood'), ('strictly', 'prohibited'), ('eddie', 'jan
zen'), ('sg', 'marshall'), ('gregg', 'lenart'), ('louis', 'dreyfus'), ('steven', 'gullion'), ('nel
son', 'ferries'), ('anniversary', 'celebration'), ('seasonal', 'differential')]
Wall time: 7.28 s
```

Typical Frequency Scores for SPAM and HAM bigrams

- Distributional statistics computed using mean and median bigram scores

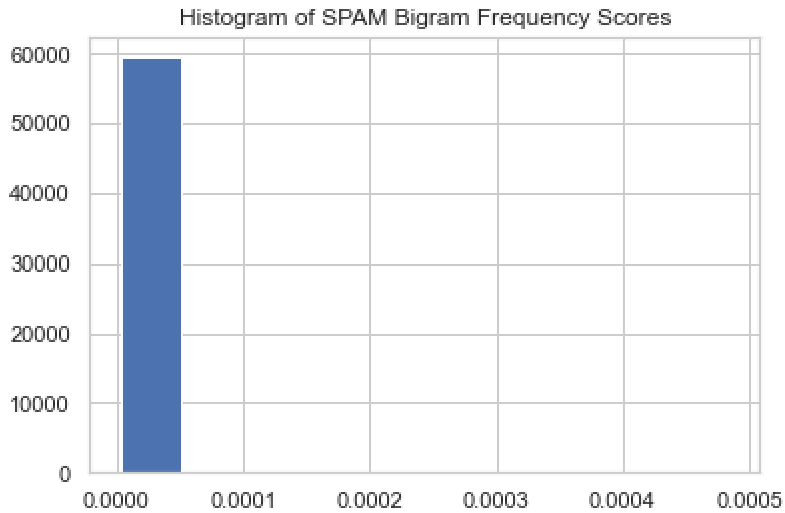
In [112…

```
mean_score_freq_spam = np.mean([s[1] for s in bigramSpamFreq])
median_score_freq_spam = np.median([s[1] for s in bigramSpamFreq])
print("SPAM frequency scores:\n")
print("Mean: {:.2E} Median: {:.2E}".format(mean_score_freq_spam, median_score_freq_spam))
mean_score_freq_ham = np.mean([s[1] for s in bigramHamFreq])
median_score_freq_ham = np.median([s[1] for s in bigramHamFreq])
print("\nHAM frequency scores:\n")
print("Mean: {:.2E} Median: {:.2E}".format(mean_score_freq_ham, median_score_freq_ham))
```

```
SPAM frequency scores:

Mean: 4.13E-06 Median: 2.81E-06

HAM frequency scores:

Mean: 3.47E-06 Median: 1.20E-06
```

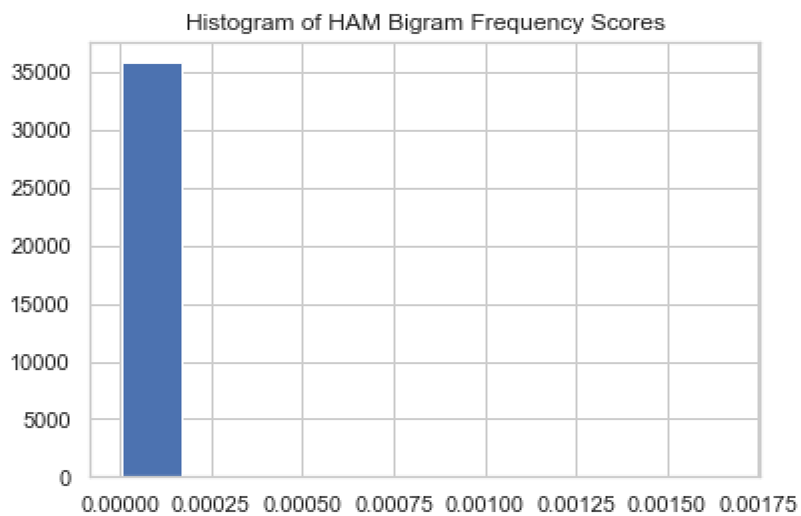
In [113…

```
a = [s[1] for s in bigramSpamFreq]
plt.hist(a)
plt.title("Histogram of SPAM Bigram Frequency Scores")
plt.show()
```



In [114…

```
a = [s[1] for s in bigramHamFreq]
plt.hist(a)
plt.title("Histogram of HAM Bigram Frequency Scores")
plt.show()
```



Typical Mutual Information Scores for SPAM and HAM bigrams

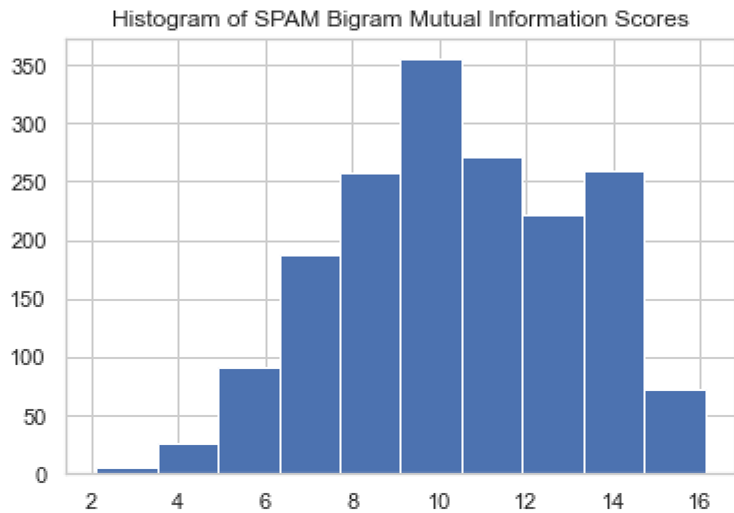
In [115…

```
mean_score_mi_spam = np.mean([s[1] for s in bigramSpamMI])
median_score_mi_spam = np.median([s[1] for s in bigramSpamMI])
print("SPAM MI scores:\n")
print("Mean: {:.2E} Median: {:.2E}".format(mean_score_mi_spam, median_score_mi_spam))
mean_score_mi_ham = np.mean([s[1] for s in bigramHamMI])
median_score_mi_ham = np.median([s[1] for s in bigramHamMI])
print("\nHAM MI scores:\n")
print("Mean: {:.2E} Median: {:.2E}".format(mean_score_mi_ham, median_score_mi_ham))
```

```
SPAM MI scores:

Mean: 1.04E+01 Median: 1.03E+01

HAM MI scores:

Mean: 8.56E+00 Median: 8.46E+00
```

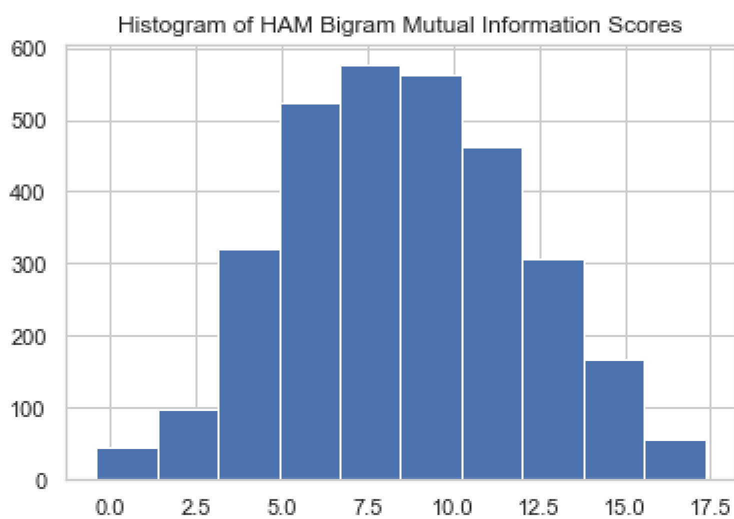
In [116…

```
a = [s[1] for s in bigramSpamMI]
plt.hist(a)
plt.title("Histogram of SPAM Bigram Mutual Information Scores")
plt.show()
```



In [117…

```
a = [s[1] for s in bigramHamMI]
plt.hist(a)
plt.title("Histogram of HAM Bigram Mutual Information Scores")
plt.show()
```



Observations:

1. Bigrams for SPAM exhibited more references to retail product entities, references to selling, and non-English phrases.
2. Bigrams for HAM exhibited more repeated references to organization, person, and location entities.
3. Bigrams for SPAM were on average more frequent than HAM by a small order of magnitude; the same could be said based on mutual information scores.
4. Frequency scores exhibit a right-skewed distribution, whereas mutual information scores feature a more normal distribution.

Actions:

1. Complete lists of bigrams were extracted for modeling and feature engineering.

Part-of-Speech Tag Frequencies for SPAM

- Assess for nouns, verbs, adjectives, and adverbs

In [118…

```
# function to print normalized frequencies of POS tags
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# prints normalized frequencies for nouns, verbs, adjectives, and adverbs
def getPosStats(documents):
    docs = documents
    # get list of tags
    pos = [t[1] for t in nltk.pos_tag(docs)]
    # aggregate class counts
    noun_count, verb_count, adj_count, adv_count = 0, 0, 0, 0
    for tag in pos:
        if tag.startswith('N'): noun_count += 1
        if tag.startswith('V'): verb_count += 1
        if tag.startswith('J'): adj_count += 1
        if tag.startswith('R'): adv_count += 1
    # normalize class counts
    noun_count_norm = noun_count / len(pos); print("Normalized Noun Frequency: {:.2f}".format(nour
    verb_count_norm = verb_count / len(pos); print("Normalized Verb Frequency: {:.2f}".format(verb
    adj_count_norm = adj_count / len(pos); print("Normalized Adjective Frequency: {:.2f}".format(a
    adv_count_norm = adv_count / len(pos); print("Normalized Adverb Frequency: {:.2f}".format(adv_
```

In [119…

```
%%time
getPosStats(spamTokens)
```

```
Normalized Noun Frequency: 0.58
Normalized Verb Frequency: 0.15
Normalized Adjective Frequency: 0.20
Normalized Adverb Frequency: 0.03
Wall time: 20.4 s
```

Part-of-Speech Tag Frequencies for HAM

- Assess for nouns, verbs, adjectives, and adverbs

In [120…

```
%%time
getPosStats(hamTokens)
```

```
Normalized Noun Frequency: 0.57
Normalized Verb Frequency: 0.19
Normalized Adjective Frequency: 0.18
Normalized Adverb Frequency: 0.03
Wall time: 37.1 s
```

Observations:

- At an aggregate level, both SPAM and HAM appear to be similar in their POS frequency distributions.
- SPAM tokens contain slightly more nouns and adjectives, and fewer verbs. ### Actions:

Include POS tag features in the modeling experimentation

Modeling Experiments

- Feature Engineering
  - ngrams (bag of words)
    ```
    - unigrams
     - bigrams
    ```
  - word statistics (lexical richness/email, # characters/email, # words/email, mean # of characters per word)
  - POS tag features ## Modeling
- Multinomial NB Sci-kit Learn
- SVM Sci-kit Learn
- Logistic Regression Sci-kit Learn

Combined list of tokenized documents

In [121…

```
# combine labeled documents
print("There are {:d} SPAM documents and {:d} HAM documents".format(len(spamDocs), len(hamDocs)))
documents = spamDocs + hamDocs
print("There are a total of {:d} documents".format(len(documents)))
```

```
There are 1500 SPAM documents and 3672 HAM documents
There are a total of 5172 documents
```

Randomly shuffle the documents for training and testing classifiers

In [122…

```
random.seed(111)
random.shuffle(documents)
print([doc[1] for doc in documents[:20]]) # demonstrate labels have been shuffled
```

```
['spam', 'ham', 'ham', 'ham', 'spam', 'ham', 'ham', 'ham', 'ham', 'spam', 'ham', 'ham', 'spam', 'h
am', 'ham', 'ham', 'ham', 'spam', 'ham', 'spam']
```

Experiment 1: Testing the Application of Stopwords

The objective of this experiment is to test whether the application of an extensive stopwords list provides for improved classification results relative to a basic stopwords list from NLTK.

The extensive stopwords list contains 28056 words and includes:

1. basic stopwords
2. high-frequency words that are common to both classes
3. hapaxes
4. Features: 3000 Unigrams

Top 3000 words based on frequency varied by the stopwords applied Classifier: Naive Bayes Classifier from NLTK

Classifier: Naive Bayes Classifier from NLTK

In [123…

```
# function to get word features
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# param stopwords: a list of strings where each element is a stopword
# returns a list of 3000 strings where each string is a word feature
def getWordFeatures(documents, stopwords):
    # lower-case conversion of complete document tokenization
    all_words_list = [word.lower() for (email, cat) in documents for word in email]
    # filter for alphabetic words
    all_words_list = [word for word in all_words_list if not alpha_filter(word)]
    # exclude stopwords
    keep_words = set(all_words_list) - set(stopwords)
    all_words_list = [word for word in all_words_list if word in keep_words]
    all_words = FreqDist(all_words_list)
    # get the 1500 most frequently appearing keywords in all words
    word_items = all_words.most_common(3000)
    word_features = [word for (word, count) in word_items]
    return word_features

# [feature definition function: experiment 1] function to get document features (applicable for un
# param document: a list of strings representing a tokenized email
# param word_features: a list of strings against which the tokens in document are matched
# returns a dictionary where each key is 'contains(keyword)' and is either true or false
def document_features(document, word_features):
    document_words = set(document)
    features = {}
    for word in word_features:
        features['V_{}'.format(word)] = (word in document_words)
    return features

# function to get feature sets for modeling in Experiment 1
def getFeatureSets1(documents, stopwords):
    # get word features based on specified stopwords
    word_features = getWordFeatures(documents, stopwords)
    featuresets = [(document_features(d, word_features), c) for (d, c) in documents]
    return featuresets
```

Feature Extraction

Two Unigram feature sets that either use basic or extensive stopwords lists

- unigramBasic3000 uses 3000 word features having excluded basic stopwords (i.e. out-of-box NLTK)
- unigramExt3000 uses 3000 word features having excluded extensive stopwords (i.e. basic stopwords, highly common keywords, hapaxes)

In [124…

```
%%time
# get feature sets for documents using basic stopwords
unigramBasic3000 = getFeatureSets1(documents, stopwords1)
# split training and test sets 70/30
unigramBasic3000Train = unigramBasic3000[:3620]
unigramBasic3000Test = unigramBasic3000[3620:]
```

```
Wall time: 45 s
```

In [125…

```
%%time
# get feature sets for documents using extensive stopwords
unigramExt3000 = getFeatureSets1(documents, stopwords2)
```

```
# split training and test sets 70/30
unigramExt3000Train = unigramExt3000[:3620]
unigramExt3000Test = unigramExt3000[3620:]
```

```
Wall time: 50.3 s
```

Functions to Train Classifier with cross-validation: Naive Bayes Classifier in NLTK

Compute Precision, Recall, F1 and Plot Confusion Matrix

In [126…

```
# function to compute precision, recall, and f1 for each label and for any number of labels
# param gold: list of strings where each element is a gold label
# param predicted: list of strings where each element is a predicted label (in same order)
# output: prints precision, recall, f1 for each class
def eval_measures(gold, predicted):
    # get a list of labels
    labels = list(set(gold))
    # initialize list of class-specific scores
    precision_list, recall_list, f1_list = [],[],[]
    for lab in labels:
        # for each label, compare gold and predicted lists and compute values
        TP = FP = FN = TN = 0
        for i, val in enumerate(gold):
            if val == lab and predicted[i] == lab:  TP += 1
            if val == lab and predicted[i] != lab:  FN += 1
            if val != lab and predicted[i] == lab:  FP += 1
            if val != lab and predicted[i] != lab:  TN += 1
        # formulas for precision, recall, and f1
        precision = TP / (TP + FN)
        recall = TP / (TP + FP)
        precision_list.append(precision)
        recall_list.append(recall)
        f1_list.append( 2 * (recall * precision) / (recall + precision))
    # the evaluation measures in a table with one row per label
    print('class\tPrecision\tRecall\tF1\n')
    # print measures for each label
    for i, lab in enumerate(labels):
        print(lab, '\t', "{:10.3f}".format(precision_list[i]), \
          "{:10.3f}".format(recall_list[i]), "{:10.3f}".format(f1_list[i]))

# function to perform cross-validation and model evaluation for experiment 1
# param num_folds: integer specifying number of iterations
# param featuresets: list containing dictionary of features and label where each element is an ema
# output: prints iteration accuracy and the mean accuracy
def cross_validation_accuracy(num_folds, featuresets):
    subset_size = int(len(featuresets)/num_folds)
    print('Each fold size:', subset_size, '\n')
    accuracy_list = []
    # iterate over the folds
    for i in range(num_folds):
        test_this_round = featuresets[(i*subset_size):][:subset_size]
        train_this_round = featuresets[:(i*subset_size)] + featuresets[((i+1)*subset_size):]
        # train using train_this_round
        classifier = nltk.NaiveBayesClassifier.train(train_this_round)
        # evaluate against test_this_round and save accuracy
        accuracy_this_round = nltk.classify.accuracy(classifier, test_this_round)
        print (i, 'accuracy:', accuracy_this_round)
        accuracy_list.append(accuracy_this_round)
```

```
    # find mean accuracy over all rounds
    print ('mean accuracy', sum(accuracy_list) / num_folds)

# function to plot confusion matrix
# param gold: list of strings where each element is a gold label
# param predicted: list of strings where each element is a predicted label (in same order)
# output: plots confusion matrix with sklearn
def getCM(gold, predicted):
    from sklearn.metrics import confusion_matrix
    cm = confusion_matrix(gold, predicted)
    # plot heatmap
    class_names=[0,1] # name  of classes
    fig, ax = plt.subplots()
    tick_marks = np.arange(len(class_names))
    plt.xticks(tick_marks, class_names)
    plt.yticks(tick_marks, class_names)
    sns.heatmap(pd.DataFrame(cm), annot=True, cmap = "YlGnBu", fmt = 'g')
    ax.xaxis.set_label_position("top")
    plt.tight_layout()
    plt.title('Confusion matrix', y=1.1)
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')

# function to produce precision, recall, f1, and confusion matrix
# param train: training set
# param test: test set
# output: prints precision, recall, f1, and plots a confusion matrix
def getClassScores(train, test):
    # train a classifier
    classifier = nltk.NaiveBayesClassifier.train(train)
    # get actuals and predictions
    goldlist, predictedlist = [],[]
    for (features, label) in test:
        goldlist.append(label)
        predictedlist.append(classifier.classify(features))
    # print evaluation measures
    eval_measures(goldlist, predictedlist)
    # plot confusion matrix
    getCM(goldlist, predictedlist)
```

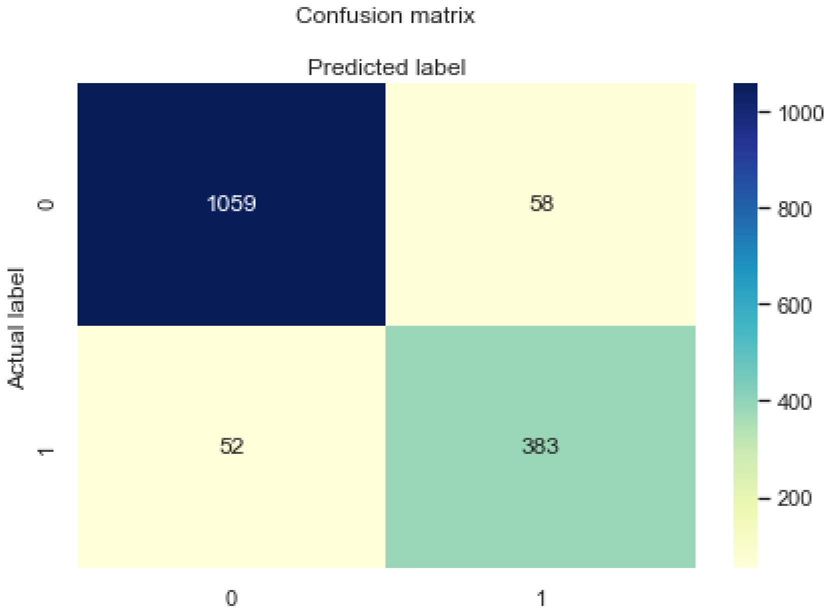
Model Evaluation: Basic Stopwords List

In [127…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, unigramBasic3000Train)
# train a classifier and predict test set; get evaluation metrics; plot confusion matrix
getClassScores(unigramBasic3000Train, unigramBasic3000Test)
```

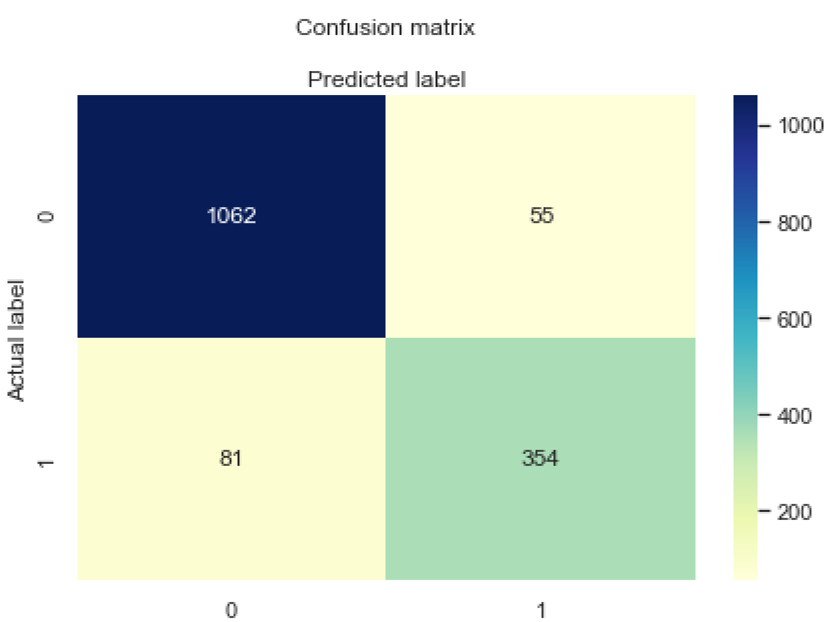
```
Each fold size: 724

0 accuracy: 0.930939226519337
1 accuracy: 0.9337016574585635
2 accuracy: 0.9323204419889503
3 accuracy: 0.9157458563535912
4 accuracy: 0.9419889502762431
mean accuracy 0.930939226519337
class   Precision       Recall  F1

ham           0.948      0.953      0.951
```

```
spam         0.880      0.868      0.874
Wall time: 3min 43s
```




```
In [128…
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, unigramExt3000Train)
# train a classifier and predict test set; get evaluation metrics; plot confusion matrix
getClassScores(unigramExt3000Train, unigramExt3000Test)
```

```
Each fold size: 724

0 accuracy: 0.9212707182320442
1 accuracy: 0.9116022099447514
2 accuracy: 0.919889502762431
3 accuracy: 0.9033149171270718
4 accuracy: 0.9433701657458563
mean accuracy 0.9198895027624309
class   Precision      Recall  F1

ham          0.951      0.929      0.940
spam         0.814      0.866      0.839
Wall time: 3min 46s
```



Experiment 2: Testing the Effectiveness of Bigrams

The objective of this experiment is to test whether adding bigrams provides for improved classification results relative to just utilizing unigrams.

Baseline featureset:

- Top 3000 unigrams by frequency with basic stopwords applied, as demonstrated in Experiment 1 Test featureset:
- Top 3000 unigrams by frequency with basic stopwords exclusion
- Top 1000 bigrams scored by frequency with basic stopwords exclusion Classifier: Naive Bayes Classifier from NLTK

Classifier: Naive Bayes Classifier from NLTK

In [129…

```
# function to get bigram features
# param documents: a list of tuples where the first item of each tuple is the tokenized email text
# param stopwords: a list of strings where each element is a stopword
# returns a list of 1000 tuples where each element is a bigram feature
def getBigramFeatures(documents, stopwords):
    # lower-case conversionof complete document tokenization
    all_words_list = [word.lower() for (email, cat) in documents for word in email]
    # Top 1000 bigram feature extraction
    measures = BigramAssocMeasures()
    finder = BigramCollocationFinder.from_words(all_words_list) # scorer
    finder.apply_word_filter(alpha_filter) # exclude non-alphabetic words
    finder.apply_word_filter(lambda w: w in stopwords) # exclude stop words
    scored = finder.score_ngrams(measures.raw_freq)
    bigram_features = [s[0] for s in scored[:1000]]
    return bigram_features

# [feature definition function: experiment 2] function to get document features (applicable for un
# param document: a list of strings representing a tokenized email
# param word_features: a list of strings against which the tokens in document are matched
# param bigram_features: a list of tuples where each element is a bigram
# returns a dictionary where each key is 'contains(keyword)' and is either true or false
def bigram_document_features(document, word_features, bigram_features):
    document_words = set(document)
    document_bigrams = nltk.bigrams(document)
    features = {}
    for word in word_features:
        features['V_{}'.format(word)] = (word in document_words)
    for bigram in bigram_features:
        features['B_{}_{}'.format(bigram[0], bigram[1])] = (bigram in document_bigrams)
    return features

# function to get feature sets for modeling in Experiment 2
def getFeatureSets2(documents, stopwords):
    # get word features based on specified stopwords
    word_features = getWordFeatures(documents, stopwords)
    # get bigram features based on specified stopwords
    bigram_features = getBigramFeatures(documents, stopwords)
    featuresets = [(bigram_document_features(d, word_features, bigram_features), c) for (d, c) in
    return featuresets
```

Feature Extraction

Two feature sets that either use unigrams only or unigrams + bigrams

- unigramBasic3000 uses 3000 word features having excluded basic stopwords (defined in Experiment 1)
- bigramBasic4000 uses 3000 word features and 1000 bigram features having excluded basic stopwords

In [130…

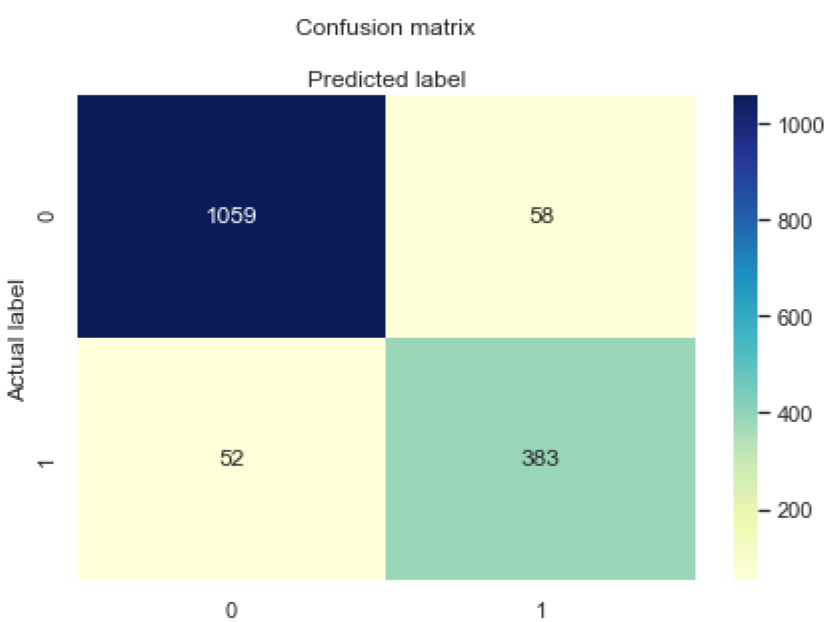
```
%%time
# get feature sets for documents using basic stopwords
bigramBasic4000 = getFeatureSets2(documents, stopwords1)
# split training and test sets 70/30
bigramBasic4000Train = bigramBasic4000[:3620]
bigramBasic4000Test = bigramBasic4000[3620:]
```

```
Wall time: 1min 9s
```

In [131…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, unigramBasic3000Train)
# train a classifier and predict test set; get evaluation metrics; plot confusion matrix
getClassScores(unigramBasic3000Train, unigramBasic3000Test)
```

```
Each fold size: 724

0 accuracy: 0.930939226519337
1 accuracy: 0.9337016574585635
2 accuracy: 0.9323204419889503
3 accuracy: 0.9157458563535912
4 accuracy: 0.9419889502762431
mean accuracy 0.930939226519337
class    Precision       Recall   F1

ham            0.948      0.953      0.951
spam           0.880      0.868      0.874
Wall time: 3min 52s
```

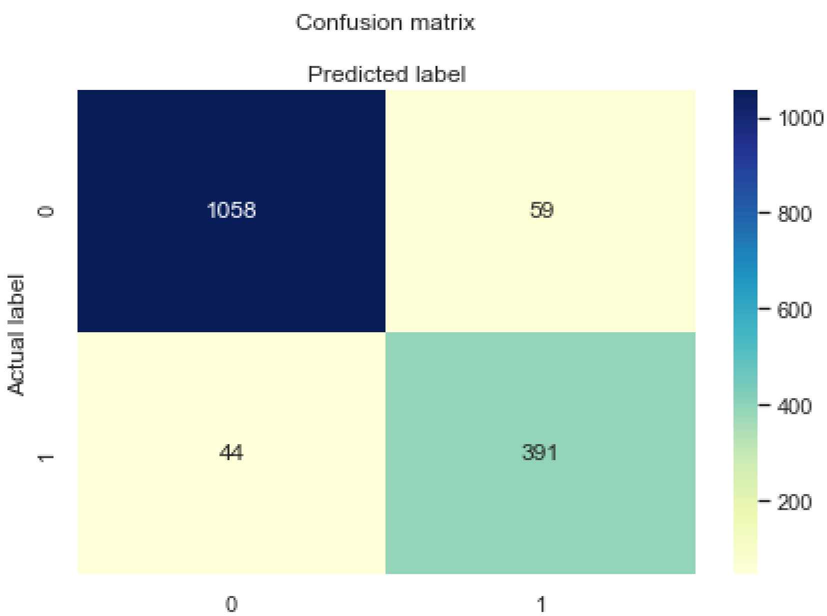


Model Evaluation: Unigrams + Bigrams

In [132…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, bigramBasic4000Train)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(bigramBasic4000Train, bigramBasic4000Test)
```

```
Each fold size: 724

0 accuracy: 0.9323204419889503
1 accuracy: 0.9337016574585635
2 accuracy: 0.9323204419889503
3 accuracy: 0.9185082872928176
4 accuracy: 0.9419889502762431
mean accuracy 0.9317679558011049
class    Precision        Recall   F1

ham            0.947      0.960      0.954
spam           0.899      0.869      0.884
Wall time: 5min 13s
```



Experiment 3: Testing the Effectiveness of Part-of-Speech Tags

The objective of this experiment is to test whether adding POS tags provides for improved classification results relative to utilizing unigrams and bigrams. In earlier exploration of POS tag frequencies for SPAM and HAM documents, it was discovered that SPAM documents generally had higher frequencies of nouns and adjectives, and lower frequencies of verbs. This was gleaned at a corpus level, but this experiment will extract features at a document level to determine if they are useful for identifying SPAM.

Baseline featureset:

- Top 3000 unigrams and top 1000 bigrams based on frequency with basic stopwords applied, as demonstrated in Experiment 2

Test featureset:

- Top 3000 unigrams by frequency with basic stopwords exclusion
- Top 1000 bigrams scored by frequency with basic stopwords exclusion

- Normalized POS tag frequency (no stopwords removed) that aggregates for nouns, verbs, adjectives, and adverbs
  - The default NLTK (Stanford) tagger will be used
  - POS tags are known to be effective in certain circumstances such as with shorter sentence-level or social media posts (e.g. tweets) Classifier: Naive Bayes Classifier

In [133…

```
# [feature definition function: experiment 3] function to get document features (applicable for un
# param document: a list of strings representing a tokenized email
# param word_features: a list of strings against which the tokens in document are matched
# param bigram_features: a list of tuples where each element is a bigram
# returns a dictionary where each key value is either 'contains(keyword)' and boolean or normalize
def pos_document_features(document, word_features, bigram_features):
    document_words = set(document) # unigrams
    document_bigrams = nltk.bigrams(document) # bigrams
    document_pos = [t[1] for t in nltk.pos_tag(document)] # pos tags
    features = {}
    # unigram features
    for word in word_features:
        features['V_{}'.format(word)] = (word in document_words)
    # bigram features
    for bigram in bigram_features:
        features['B_{}_{}'.format(bigram[0], bigram[1])] = (bigram in document_bigrams)
    # pos features
    noun_count, verb_count, adj_count, adv_count = 0, 0, 0, 0
    for tag in document_pos:
        if tag.startswith('N'): noun_count += 1
        if tag.startswith('V'): verb_count += 1
        if tag.startswith('J'): adj_count += 1
        if tag.startswith('R'): adv_count += 1
    features['noun_count_norm'] = noun_count / len(document_pos)
    features['verb_count_norm'] = verb_count / len(document_pos)
    features['adj_count_norm'] = adj_count / len(document_pos)
    features['adv_count_norm'] = adv_count / len(document_pos)
    return features

# function to get feature sets for modeling in Experiment 2
def getFeatureSets3(documents, stopwords):
    # get word features based on specified stopwords
    word_features = getWordFeatures(documents, stopwords)
    # get bigram features based on specified stopwords
    bigram_features = getBigramFeatures(documents, stopwords)
    featuresets = [(pos_document_features(d, word_features, bigram_features), c) for (d, c) in doc
    return featuresets
```

Feature Extraction

- Two feature sets that either use (unigrams + bigrams) or (unigrams + bigrams + normalized pos tag frequencies)
  - bigramBasic4000 uses 3000 word features and 1000 bigram features having excluded basic stopwords (defined in Experiment 2)
  - posBasic4000 uses 3000 word features, 1000 bigram features (as defined in Experiment 2), and 4 additional pos tag features

In [134…

```
%%time
# get feature sets for documents using basic stopwords
```

```
posBasic4000 = getFeatureSets3(documents, stopwords1)
# split training and test sets 70/30
posBasic4000Train = posBasic4000[:3620]
posBasic4000Test = posBasic4000[3620:]
```

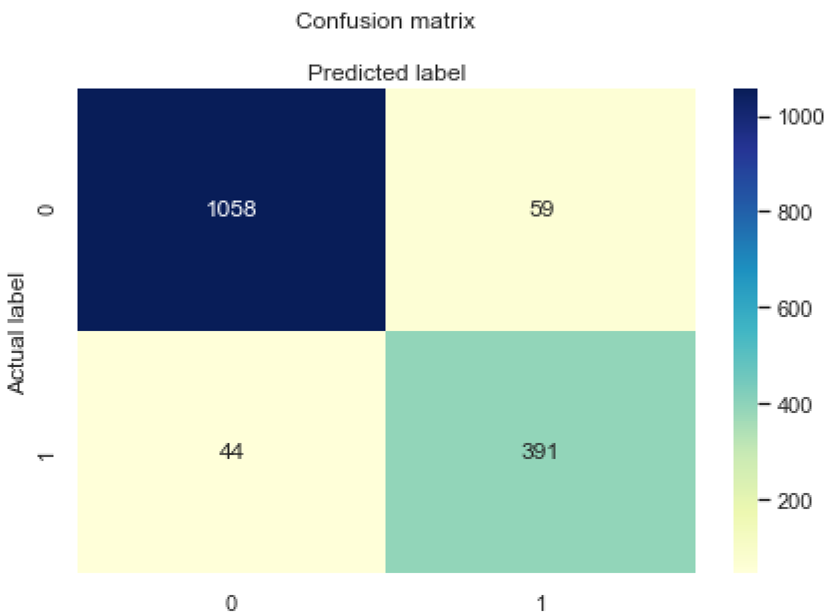
```
Wall time: 2min 50s
```

Model Evaluation: Unigrams + Bigrams

In [135…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, bigramBasic4000Train)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(bigramBasic4000Train, bigramBasic4000Test)
```

```
Each fold size: 724

0 accuracy: 0.9323204419889503
1 accuracy: 0.9337016574585635
2 accuracy: 0.9323204419889503
3 accuracy: 0.9185082872928176
4 accuracy: 0.9419889502762431
mean accuracy 0.9317679558011049
class   Precision       Recall  F1

ham             0.947      0.960      0.954
spam            0.899      0.869      0.884
Wall time: 4min 56s
```



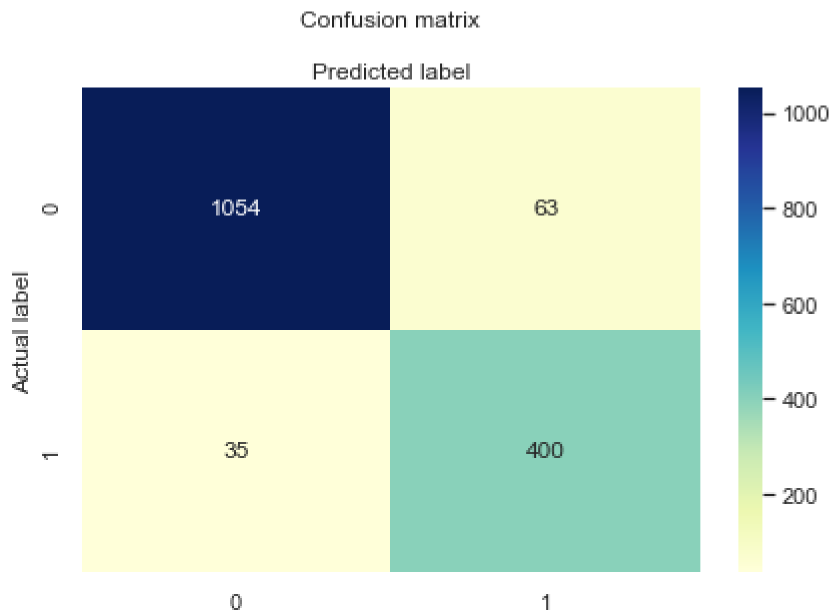
Model Evaluation: Unigrams + Bigrams + POS Tags

In [136…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, posBasic4000Train)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(posBasic4000Train, posBasic4000Test)
```

```
Each fold size: 724
```

```
0 accuracy: 0.9378453038674033
1 accuracy: 0.9378453038674033
2 accuracy: 0.93646408839779
3 accuracy: 0.9212707182320442
4 accuracy: 0.9475138121546961
mean accuracy 0.9361878453038674
class    Precision       Recall   F1

ham            0.944      0.968      0.956
spam           0.920      0.864      0.891
Wall time: 5min 8s
```



Experiment 4: Additional Corpus Statistics as Features

The objective of this experiment is to test whether adding certain corpus statistics provides for improved classification results, where the "corpus" in this context is an email. In earlier exploration it was observed that SPAM emails were generally longer than HAM emails and contain more unique words. They also measured higher in lexical richness.

Lexical richness, character count, and mean word length will be the features to include and test:

1. Lexical richness is the ratio of unique word count to total word count
2. Character count is the total number of characters in the email
3. Mean word length is the average number of characters per word for every word in the email
4. For the purposes of this experiment, stopwords will not be removed for the extraction of these three features.

Baseline featureset:

1. 3000 unigrams, 1000 bigrams, and POS tags as defined in Experiment 3

Test featureset:

1. Top 3000 unigrams by frequency with basic stopwords exclusion
2. Top 1000 bigrams scored by frequency with basic stopwords exclusion

3. Normalized POS tag frequency (no stopwords removed) that aggregates for nouns, verbs, adjectives, and adverbs using the default NLTK (Stanford) tagger
4. Lexical richness, email character count, and mean word length

Classifier: Naive Bayes Classifier

In [137…

```
# [feature definition function: experiment 4] function to get document features
# param document: a list of strings representing a tokenized email
# param word_features: a list of strings against which the tokens in document are matched
# param bigram_features: a list of tuples where each element is a bigram
# returns a dictionary where each key value is either 'contains(keyword)', normalized frequencies
def document_features4(document, word_features, bigram_features):
    document_words = set(document) # unigrams
    document_bigrams = nltk.bigrams(document) # bigrams
    document_pos = [t[1] for t in nltk.pos_tag(document)] # pos tags
    features = {}
    # unigram features
    for word in word_features:
        features['V_{}'.format(word)] = (word in document_words)
    # bigram features
    for bigram in bigram_features:
        features['B_{}_{}'.format(bigram[0], bigram[1])] = (bigram in document_bigrams)
    # pos features
    noun_count, verb_count, adj_count, adv_count = 0, 0, 0, 0
    for tag in document_pos:
        if tag.startswith('N'): noun_count += 1
        if tag.startswith('V'): verb_count += 1
        if tag.startswith('J'): adj_count += 1
        if tag.startswith('R'): adv_count += 1
    features['noun_count_norm'] = noun_count / len(document_pos)
    features['verb_count_norm'] = verb_count / len(document_pos)
    features['adj_count_norm'] = adj_count / len(document_pos)
    features['adv_count_norm'] = adv_count / len(document_pos)
    # corpus statistics
    features['lexical_richness'] = len(document_words) / len(document) # lexical richness of email
    features['total_char_count'] = 0 # total character count of email
    for word in document:
        features['total_char_count'] += len(word)
    word_lengths = [len(word) for word in document]
    features['mean_word_length'] = sum(word_lengths) / len(word_lengths) # mean word length of ema
    return features

# function to get feature sets for modeling in Experiment 2
def getFeatureSets4(documents, stopwords):
    # get word features based on specified stopwords
    word_features = getWordFeatures(documents, stopwords)
    # get bigram features based on specified stopwords
    bigram_features = getBigramFeatures(documents, stopwords)
    featuresets = [(document_features4(d, word_features, bigram_features), c) for (d, c) in docume
    return featuresets
```

Feature Extraction

- Two feature sets that either use (unigrams + bigrams + normalized pos tag frequencies) or (unigrams + bigrams + normalized pos tag frequencies + corpus statistics).
  - posBasic4000 uses 3000 word features, 1000 bigram features (as defined in Experiment 2), and 4 additional pos tag features (defined in Experiment 3).

- corpStats includes features defined in Experiment 3 as well as additional corpus statistics.

In [138…

```
%%time
# get feature sets for documents using basic stopwords
corpStats = getFeatureSets4(documents, stopwords1)
# split training and test sets 70/30
corpStatsTrain = corpStats[:3620]
corpStatsTest = corpStats[3620:]
```

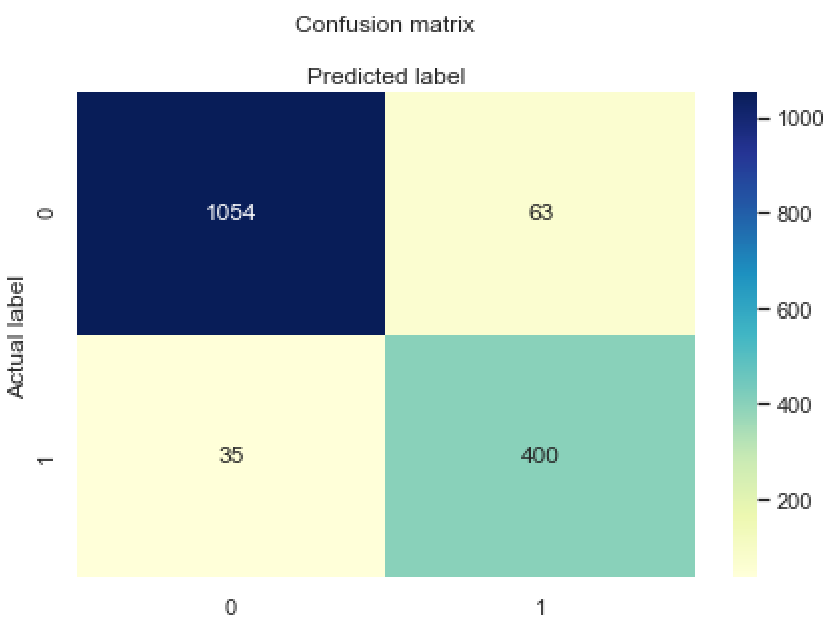
```
Wall time: 2min 11s
```

Model Evaluation: Unigrams + Bigrams + POS Tags

In [139…

```
%%time
# 5-fold cross-validation on training set
cross_validation_accuracy(5, posBasic4000Train)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(posBasic4000Train, posBasic4000Test)
```

```
Each fold size: 724

0 accuracy: 0.9378453038674033
1 accuracy: 0.9378453038674033
2 accuracy: 0.93646408839779
3 accuracy: 0.9212707182320442
4 accuracy: 0.9475138121546961
mean accuracy 0.9361878453038674
class	Precision	Recall	F1

ham		0.944	0.968	0.956
spam		0.920	0.864	0.891
Wall time: 5min 13s
```



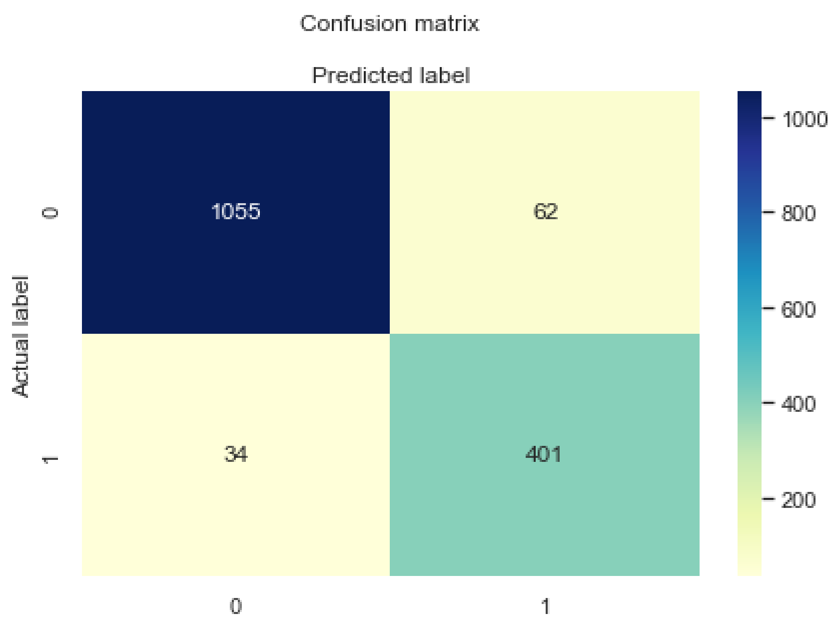
Model Evaluation: Unigrams + Bigrams + POS Tags + Corpus Statistics

In [140…

```
%%time
# 5-fold cross-validation on training set
```

```
cross_validation_accuracy(5, corpStatsTrain)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(corpStatsTrain, corpStatsTest)
```

```
Each fold size: 724

0 accuracy: 0.9378453038674033
1 accuracy: 0.9406077348066298
2 accuracy: 0.9406077348066298
3 accuracy: 0.930939226519337
4 accuracy: 0.9530386740331491
mean accuracy 0.9406077348066297
class    Precision       Recall   F1

ham           0.944      0.969      0.956
spam          0.922      0.866      0.893
Wall time: 5min 15s
```



Experiment 5: Comparison of Classification Algorithms in NLTK and Sci-Kit Learn

The objective of this experiment is to test the performance of a different classification algorithm and compare it to the best baseline model from Experiment 4. The featureset content will essentially remain unchanged, but the comparison will be on the different classifiers.

Common featureset for both classifiers:

1. Top 3000 unigrams by frequency with basic stopwords exclusion
2. Top 1000 bigrams scored by frequency with basic stopwords exclusion
3. Normalized POS tag frequency (no stopwords removed) that aggregates for nouns, verbs, adjectives, and adverbs using the default NLTK (Stanford) tagger
4. Lexical richness, email character count, and mean word length

The featureset may be formatted to an array/sparse matrix to comply with the Sci-Kit Learn classifier specifications. For the purposes of this experiment, the default modeling tuning parameters will be used.

Baseline algorithm/classifier:

1. Naive Bayes Classifier from SCI-kit Learn

Test algorithm/classifier:

1. Linear SVC (support vector classification)

Feature Set Conversion for Sci-Kit Learn Classifier

1. Using Pandas Library

In [141…

```
features = [f for (f,c) in corpStats]
labels = [c for (f,c) in corpStats]
#pandas data frame of features
X = pd.DataFrame(features)
y = np.array(labels)
#train / test split (70/30)
X_train = X.iloc[:3620, :]
X_test = X.iloc[3620:, :]
y_train = y[:3620]
y_test = y[3620:]
```

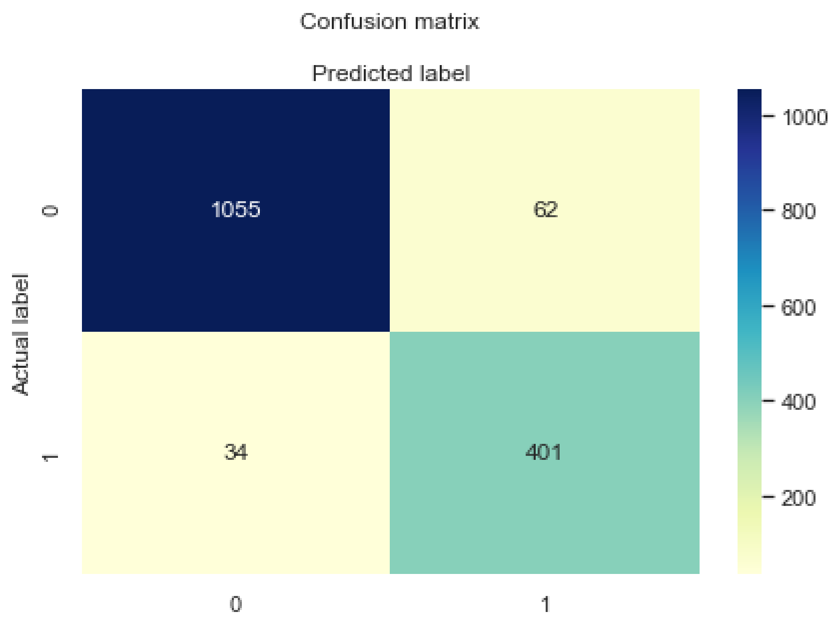
Model Evaluation: Naive Bayes Classifier from NLTK

- 10-fold cross-validation accuracy, precision, recall, F1, and confusion matrix

In [146…

```
%%time
# 10-fold cross-validation on training set
cross_validation_accuracy(10, corpStatsTrain)
# train a classifier and predict test set: get evaluation metrics; plot confusion matrix
getClassScores(corpStatsTrain, corpStatsTest)
```

```
Each fold size: 362

0 accuracy: 0.9475138121546961
1 accuracy: 0.925414364640884
2 accuracy: 0.9447513812154696
3 accuracy: 0.9502762430939227
4 accuracy: 0.930939226519337
5 accuracy: 0.9447513812154696
6 accuracy: 0.9337016574585635
7 accuracy: 0.9337016574585635
8 accuracy: 0.9613259668508287
9 accuracy: 0.9447513812154696
mean accuracy 0.9417127071823204
class    Precision       Recall   F1

ham           0.944      0.969      0.956
spam          0.922      0.866      0.893
Wall time: 8min 34s
```



In [150…

```
# please disegard the model from Naive Bayes
from sklearn.model_selection import cross_val_predict
from sklearn.metrics import confusion_matrix
clf = MultinomialNB()
y_pred = cross_val_predict(clf, X_train, y_train, cv=10)
```

In [151…

```
print(classification_report(y_train, y_pred))
```

```
              precision    recall  f1-score   support

         ham       0.98      0.95      0.96      2558
        spam       0.89      0.95      0.92      1062

    accuracy                           0.95      3620
   macro avg       0.93      0.95      0.94      3620
weighted avg       0.95      0.95      0.95      3620
```

Model Evaluation: Linear SVC from Sci-Kit Learn

10-fold cross-validation accuracy, precision, recall, F1, and confusion matrix

In [152…

```
%%time
# train classifier
classifier = LinearSVC(C=1, penalty='l1', dual=False, class_weight='balanced')
# 10-fold cross-validation on training set
np.random.seed(111)
y_pred = cross_val_predict(classifier, X_train, y_train, cv=10)
```

```
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
```

```
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
C:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:986: ConvergenceWarning: Liblinear failed to c
onverge, increase the number of iterations.
  "the number of iterations.", ConvergenceWarning)
Wall time: 20 s
```

In [153…

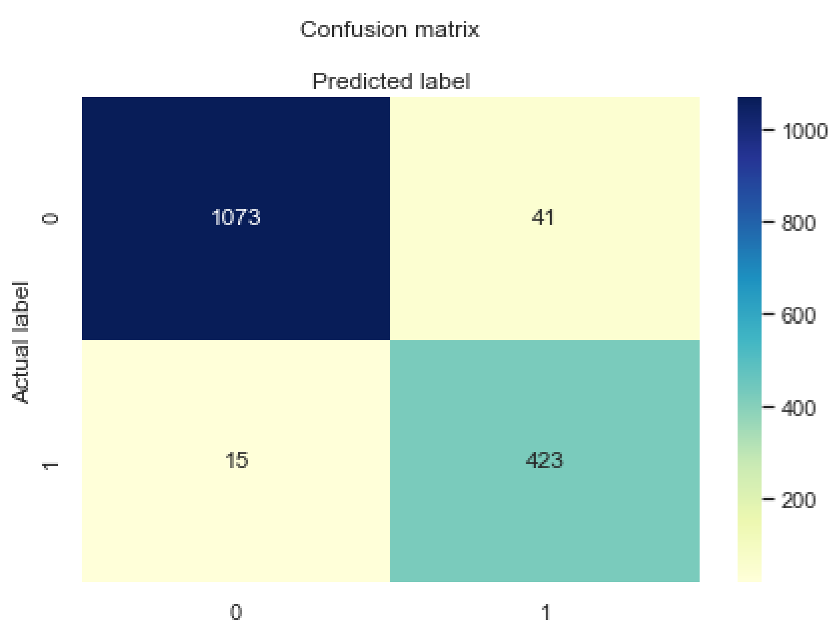
```
# classification report of cross validation results from training set
print(classification_report(y_train, y_pred))
```

```
              precision    recall  f1-score   support

         ham       0.98      0.97      0.97      2558
        spam       0.92      0.96      0.94      1062

    accuracy                           0.96      3620
   macro avg       0.95      0.96      0.96      3620
weighted avg       0.97      0.96      0.97      3620
```

In [154…

```
%%time
# train classifer to predict test set
svm = classifier.fit(X_train, y_train)
preds = svm.predict(X_test)
# evaluation measures
eval_measures(y_test, preds)
getCM(y_test, preds)
```

```
class   Precision       Recall  F1

ham            0.963      0.986      0.975
spam           0.966      0.912      0.938
Wall time: 2.56 s
```



Results

Noteworthy observations from exploration:

- On a per email basis, SPAM emails are generally longer than HAM emails and contain more unique words.
- SPAM emails measure higher in lexical richness than HAM emails.
- Term frequency distributions for SPAM and HAM show a distinction. It is clear that the top 50 words for HAM make up a greater proportion of its total word frequency relative to SPAM. The top 50 - 100 words for SPAM and HAM seemed to be mutually exclusive for the most part. It is learned later in experiments that mutually exclusive terms are not necessary what distinguishes SPAM and HAM, but rather the way in which terms are used in sentence formation. See Experiment 1.

A note on bigrams:

- Bigrams for SPAM exhibited more references to retail product entities, selling, and non-English phrases.
- Bigrams for HAM exhibited more repeated references to organization, person, and location entities.
- Bigrams for SPAM were on average more frequent than HAM by a small order of magnitude; the same could be said based on mutual information scores.
- SPAM tokens contained more nouns and adjectives, and fewer verbs. However, overall frequency distributions for POS tags appeared similar.

Experiment 1: Which Stopwords are Most Effective?

- Two feature sets were created from unigrams that used either a basic stopwords list or an extensive stopwords list.
- The basic stopwords list only included the out-of-box English stopwords provided in NLTK. The extensive stopwords list included the same but also added high frequency words that were common to both SPAM and HAM, as well as hapaxes (highly infrequent words) for SPAM and HAM.
- A comparison of mean accuracies from cross-validation of the two unigram feature sets using the NLTK Naive Bayes Classifier show that using minimal stopwords improved mean accuracy by about 1 percentage points. The extensive stopwords list was not useful in improving classification accuracy.
- Mean accuracy was recorded at 92-93%. Class-specific precision, recall, and f1 shows that in all cases, the model is better at predicting HAM than SPAM. This is most likely due to the imbalanced data, where there are significantly more HAM observations than SPAM observations.

Takeaway: Basic stopwords worked best in terms of model accuracy and overall performance (including speed)

Experiment 2: Effect of Bigram Inclusion to the Featureset

- In this experiment, two feature sets were compared based on classification accuracy and other evaluation measures. One feature set used unigrams exclusively to train a SPAM classifier, whereas the other used both unigrams and bigrams. Both feature sets applied basic stopwords during the feature extraction process
- Model evaluation based on the unigram feature set showed the same results as seen in Experiment 1 with an overall mean accuracy of about 93%. Precision, recall, and f1 specific to SPAM were 88%, 87%, and 87% respectively.
- Model evaluation based on the bigram feature set showed improved classification results with a slightly higher mean accuracy of about 93.2%. There were noticeable improvements in the precision, recall, and f1

specific to SPAM, which presents this model as a better SPAM classifier than the unigram-only model.

Takeaway: Bigram features gave the model an added boost, particularly in predicting SPAM emails.

Experiment 3: Effect of POS Tag Inclusion to the Featureset

- This experiment was conducted to measure the effect of adding POS tag features to the (unigram, bigram) feature set defined in experiment 2.
- Part-of-Speech tags were extracted from each email and frequencies of nouns, verbs, adjectives, and adverbs were aggregated.
- These were then normalized by taking the ratio of the counts to the total number of tags in each email.
- Model evaluation showed clear improvements in classification as a result of the inclusion of POS tags to the baseline (unigram, bigram) feature set.
- Overall mean accuracy from cross-validation increased from 93.1% to 93.6%.
- Precision specific to SPAM increased from 89.9% to 92%; the model's positive predictions showed noticeable improvements.
- F1 scores also improved for both HAM and SPAM classes due to adding POS tags.

Takeaway: POS tag features boosted overall SPAM & HAM prediction performance, particularly for accuracy and F1 measures.

Experiment 4: Corpus Statistics and its Effects on Classifying SPAM

- During the exploration phase it was observed that on a per email basis, SPAM emails are generally longer than HAM emails and contain more unique words. SPAM emails measured higher in lexical richness than HAM emails.
- Due to this insight, it was determined that corpus statistics such as lexical richness (ratio of unique word count to total word count), total character count, and mean word length should be incorporate in the features to test their effectiveness.
- The baseline feature set to which these new features were compared against was the best feature set thus far up through Experiment 3 (i.e. unigrams + bigrams + POS tags)
- Although these measures were termed "corpus statistics", a corpus in this context is just an email from which these features are extracted.
- Model evaluation showed very promising results, perhaps as expected, in that evaluation measures increased across the board.
- Mean accuracy increased from 93.6% to 94%. Precision, recall, and F1 either remained the same or increased for classifying HAM emails. The most noticeable improvement was observed in SPAM classification where precision, recall, and F1 increased.

Takeaway: The addition of corpus statistics noticeably increased the models SPAM classification capability.

Experiment 5: Comparison of Classification Algorithms

- In this final experiment, the same feature set is applied with different classification algorithms to determine which model yields the highest evaluation measures. These measures, utilized in previous experiments, are cross-validation accuracy, precision, recall, and F1.

- The baseline algorithm was the Naive Bayes Classifier from NLTK, and the test algorithm was Linear SVC (support vector classification) from Sci-Kit Learn.
- The feature set chosen was the one which yielded the best classification results in Experiment 4. This feature set included 3000 unigrams, 1000 bigrams, POS tags, and corpus statistics.
- The Naive Bayes classifier is characterized by its estimation of class-conditional probabilities, whereas the Support Vector Machine with linear kernel (i.e. Linear SVC algorithm) generates support vectors that determine the decision boundaries respective to each class and maximizes the margins of these boundaries for generalization.
- As a result of applying the Linear SVC, model evaluation showed an improvement in cross-validation accuracy from 94.1% to 96%.
- F1 scores respective to SPAM increased substantially from 89.3% to 94%.

Takeaway: The Linear SVC from the Sci-Kit Learn library outperformed the baseline method using the Naive Bayes algorithm from NLTK both in speed and accuracy.

Conclusion

In this project, five experiments were conducted to assess the progression of improved capability in SPAM email detection. The key takeaway from these experiments was that a better detection capability comes with having a large feature set comprised of unigrams, bigrams, part-of-speech tags, and corpus statistics. The fifth and final experiment demonstrates that certain algorithms also play a key role in achieving better results. In fact, the largest increase in accuracy, across all the experiments, resulted from using a different algorithm altogether.

All of the methods used here demonstrate machine learning for anti-SPAM filtering. This extends beyond simple email filters that use keywords or regular expressions for detection. It should be disclaimed that these methods have only been trained and tested on the data provided, specifically a subset of the full Enron email corpus, and any application outside these parameters should exercise caution. The full email corpus can be found at http://www2.aueb.gr/users/ion/data/enron-spam/.

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